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Exploring China's carbon emissions peak for different carbon tax scenarios

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ABSTRACT

Under the United Nations Framework Convention on Climate Change, China has made a commitment to peak CO2 emissions around 2030. China is still interested in fulfilling its commitment to address climate change. In this study, a diffusion model of energy technology based on endogenous technology learning under bounded rationality is developed to explore the possible impacts of different carbon tax conditions on the diffusion of energy technologies in China. It is concluded that the substitution of energy technology is a long-term and slow process. In the case of a high-carbon tax, transition technologies and new technologies will appear earlier and replace the original technology (6–8 years earlier than in the case of a lower carbon tax). The transition technology will become dominant only for a short period of time (around 2030) but will be quickly replaced by new technology. The traditional technology will cease to exist in the last thirty years of this century in all carbon tax scenarios. In the low-carbon tax or high-carbon tax scenarios, carbon emissions will peak in 2030 and then decline significantly. The peak in carbon emissions is lower under the high-carbon tax scenario than the low-carbon tax scenario, representing a 28% decrease.

1. Introduction

Energy plays a significant role in the national economy and in the development of a resource-conserving and harmonious society. Governments worldwide also regard energy as an important issue. The diffusion of new technologies in the energy system has become an important focus. The diffusion effect of technology in the energy system does not only reflect the speed of technology replacement but also indirectly affects the level of carbon emissions. In 2015, China announced at the Paris Agreement that it intends to reach peak carbon dioxide emissions around 2030 and will reduce CO_2 emissions per unit gross domestic product (GDP) by 60–65% from the 2005 level (UNFCCC, 2015). Although the Chinese government's carbon emission reduction efforts have been proved to be rational and feasible in recent years, there are still different views on whether China can achieve this commitment at home and abroad. Some argued that these goals are too ambitious for the Chinese government to achieve and that the country cannot afford the cost (Elzen et al., 2016). Some even suspect that China may intentionally increase its carbon emissions over the next two decades in order to make the peak as high as possible (Malakoff, 2014), whereas other studies discussed trends in China's energy consumption and carbon dioxide emissions (ERI, 2009a; Wang and Watson, 2010; Zhou et al., 2013; BP, 2016). These results show that without any policy intervention, China's carbon emissions will continue to increase and it may be difficult to reach the peak before 2030 or the peak time may be delayed by 10–20 years, whereas others believe that the targets may not be difficult to reach and it may cost less than expected (Green and Stern, 2017; Yu et al., 2018).

Domestic and foreign scholars have conducted much research on technology diffusion models. In traditional energy system optimization models, technological changes are largely regarded as exogenous. Most of these optimization models are linear optimization models. Even if the modeling system is quite large and complex, it is easy to obtain a globally optimal solution with hundreds of energy technologies and thousands of parameters. Beginning in the mid-1990s, researchers began to study energy system optimization models that incorporated endogenous technological changes (Messner, 1997; Gritsevskyi and Nakicenovic, 2000; Kypreos et al., 2000; Grubler and Gritsevskyi, 2002). For example, Ma and Yoshiteru (2009) established an improved energy model for endogenous technology diffusion; this was an agent-based model based on bounded rationality and the model decision was adjusted according to the type of resource exhaustion and the demand dynamics that were created. The demand is not completely exogenous but is partly influenced by the agent's previous decision, which had its own advantages. However, it was assumed in this model that the resource extraction cost increased with the increase in the cumulative

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production; the improvement in mining technology and the effect of the reduction of newly-exploited resource reserves on the mining cost were ignored, making the model unreasonable. Liu et al. (2014) developed an endogenous technology energy model that considered the influence of emission reduction policies; the model described and simplified the relationship between the economic system and the energy sector and described the emission reduction mechanism of the carbon tax in the energy supply chain. Duan et al. (2015) developed the China regional energy-environment-economic endogenous technology model (CE3-METL) to investigate the cost evolution and technical development potential of carbon capture and storage (CCS) technology under different climate policy backgrounds. However, the above-mentioned two models do not consider the irrational judgment of decision makers regarding the cost of installation and the confidence of consumers in investments. Yu et al. (2018) developed a multi-objective optimized energy technology model for endogenous technology learning considering the lowest carbon emissions, the largest GDP, and the lowest energy consumption cost; it was concluded that China was most likely to reach the carbon emission peak by the end of 2028. However, it is difficult to optimize the objective function when choosing the Pareto optimal solution and the irrational behavior of the decision makers is often not considered.

The most significant feature of the endogenous technological change model is that with the continuous use of new technologies, users will become more familiar with new technologies and their technical experience will continue to increase, resulting in lower cost of investment. This so-called “technical learning” is an example that economic returns gradually increase (Arthur, 1989). An optimization model for determining endogenous technological changes is also regarded as an induced technological change model or learning by doing (LBD) model (Manne and Barreto, 2005). Compared with the traditional energy system optimization model, the advantage of this model is that technological learning is incorporated into current uneconomical technology by learning to continuously reduce costs and ultimately adopt advanced technology mechanisms. However, most of the existing endogenous technological change models are based on ideal conditions, i.e., it is assumed that decision makers make rational decisions and the influence of irrational factors is not taken into account. However, in an agent-based energy technological model, the agent can create a short-term energy demand plan based on past knowledge and future expectations. Since the model does not know everything that will occur in the future, it is boundedly rational. The energy technology diffusion model based on endogenous technology of bounded rationality used in this study retains the advantages of the endogenous technology learning model, takes into account the limited rational decision of government and investors, and more effectively and accurately reflects the actual conditions of energy technology substitution.

The structure of this paper is as follows: The first section introduces the energy technology diffusion model based on bounded rationality. The specific data and their sources are provided in Section 2. Section 3 simulates to analyze with different carbon tax conditions and then explores whether China's carbon emissions can reach its peak on time. Finally, conclusions are drawn.

2. Mathematical model

The improved endogenous technology diffusion model is based on the assumption that in order to meet the needs of future economic development and technological advancement, policymakers have developed a plan spanning 100 years for the future energy system, during which time the total cost should be minimized.

Ma and Yoshiteru (2009) intentionally simplified the energy system and established a model that considers the evolution of endogenous technology; this model assumes that energy demand needs to be measured by a reference standard (such as electricity). At the same time, the technology in this study is classified into three categories, namely existing technology, transitional technology, and revolutionary technology. The possibility of promoting the adoption of new technologies includes the capability and capacity limitations of the prior art, the gradual (exogenous) reduction of gas turbines and photovoltaic cells, and the depletion of resources. In this study, the government's restrictions on carbon emissions, the investors' confidence in new low-carbon technologies, and other factors are taken into account and a model of China's energy technology diffusion based on bounded rationality is established.

The objective function is defined as:

$$\min \sum_{i=1}^{3}\sum_{t=1}^{T} \frac{1}{(1+\delta)^t} c_{Fi}^t y_i^t + \frac{1}{(1+\delta)^t} c_{Ei}^t (1+\eta_i)^t R_i^t + \frac{1}{(1+\delta)^t} c_{OMi} x_i^t + \frac{1}{(1+\delta)^t} s p_i^t \tag{1}$$

The total cost includes investment costs, mining costs, operating and maintenance costs, and carbon tax costs.

The constraints are as follows:

$$(1+r)G_t \le G_{t+1} \tag{2}$$

$$x_i^t \le C_i^t \quad (\mathrm{t} = 1,2,\ldots,\mathrm{T})\,(\mathrm{i} = 1,2,3) \tag{3}$$

$$x_i^t \ge 0 \quad (\mathrm{t} = 1,2,\ldots,\mathrm{T})\,(\mathrm{i} = 1,2,3) \tag{4}$$

$$y_i^t \ge 0 \quad (\mathrm{t} = 1,2,\ldots,\mathrm{T})\,(\mathrm{i} = 1,2,3) \tag{5}$$

$$\mu y_i^t \ge y_i^{t+1} \quad (\mathrm{t} = 1,2,\ldots,\mathrm{T}-1)\,(\mathrm{i} = 1,2,3) \tag{6}$$

$$\omega_i^t y_i^t \le y_i^{t+1} \quad (\mathrm{t} = 1,2,\ldots,\mathrm{T}-1)\,(\mathrm{i} = 1,2,3) \tag{7}$$

T denotes the time period, which is the scale of the problem;
δ denotes the discount rate;
c_{Fi}^t denotes the cost of producing the unit capacity of technology i at time t;
c_{Ei}^t denotes the cost of mining the corresponding unit resources of technology i at time t;
G_t denotes the GDP contributed by energy consumption at time t;
R_i^t denotes the corresponding resources consumed by technology i at time t;
c_{OMi} denotes the operating and maintenance costs of technology i;
y_i^t(i = 1,2,3) denotes the newly installed capacity of technology i at time t;
x_i^t(i = 1, 2, 3) denotes the energy consumption of technology i at time t;
s denotes the carbon tax imposed on the unit's carbon dioxide emissions;
p_i^t denotes the carbon emissions of technology i at time t.
R_i^t is defined in Eq. (8), where C_i^t represents the total installed capacity of the technology i at time t and ρ_i denotes the efficiency of the technology i:

$$R_i^t = \frac{C_i^t}{\rho_i} \tag{8}$$

Equation (2) indicates that the contribution of the annual energy consumption to GDP growth cannot be less than the expected GDP growth rate. r represents the expected annual GDP growth rate and the GDP contributed by energy consumption at time t is defined in Eq. (9), where E_t is the energy intensity and is considered the energy consumption per unit of GDP.

$$G_t = \frac{x_i^t}{E_t} \tag{9}$$

Equation (3) indicates that the annual power consumption of each technology cannot exceed the installed capacity; Eqs. (4) and (5) indicate that the decision variables cannot be meaningless.

Equation (6) indicates that there is an upper limit for the newly

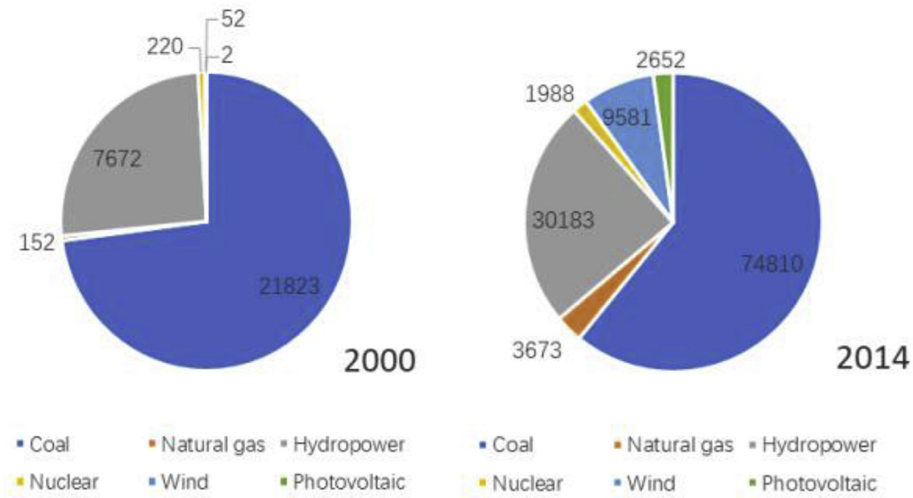

Fig. 1. Share of energy installed capacity.

added installed capacity of the technology each year. The upper limit is related to the newly added installed capacity in the previous year. μ indicates the bottleneck coefficient, which can be regarded as the limitation of the production capacity due to a lack of equipment for producing new technologies. Therefore, it is impossible to achieve explosive growth in the new technology's installed capacity in a short period of time. This coefficient can be expressed by the investors' confidence in green development, as shown in Eq. (10), where z_i represents the unit power generation of technology i. The carbon dioxide emissions λ, a fixed constant, indicate the basic investment confidence.

$$\mu = s * \frac{\frac{1}{z_i}}{\sum_{i=1}^{3}\frac{1}{z_i}} + \lambda \tag{10}$$

Equation (7) indicates that any technology has inertia in production. Even if the technology may not be dominant with regard to the actual cost, the decision maker is bounded rational and will follow the inertia of thinking (sometimes due to the incomplete transparency of the technical cost information of the three kinds of technologies in the market) and add some installed capacity of the traditional technology, where ω_i^t is the inertia factor, which is defined in Eq. (11); τ_i in Eq. (12) represents the factory lifetime of technology i:

$$\omega_i^t = \frac{C_i^t}{\sum_{i=1}^{3} C_i^t} \tag{11}$$

$$C_i^t = \sum_{j=t-\tau_i}^{T} y_i^j \tag{12}$$

Unlike in the traditional energy technology diffusion model, the investment cost of the technology does not remain unchanged or will change with the change in the exogenous depreciation rate. Accordingly, as the cumulative installed capacity of the technology increases, c_{Fi}^t will decrease, which can be regarded as the accumulated learning experience, as defined in Eq. (13):

$$c_{Fi}^t = c_{Fi}^0 \times (\overline{C}_i^t)^{-bi} \tag{13}$$

where 1-2^{-bi} is the learning rate of technology i, i.e., the percentage of the future investment cost reduced with the cumulative installed capacity multiplication. 2^{-bi} is called the progress ratio, and represents the learning efficiency. c_{Fi}^0 is the initial investment cost of technology i and $\overline{C}_i^t$ is the cumulative installed capacity of technology i at time t, indicating people's familiarity with the technology. Thus, Eq. (14) is obtained:

$$\overline{C}_i^t = \sum_{j=1}^{t} C_i^j + \overline{C}_i^0 \tag{14}$$

where $\overline{C}_i^0$ represents the initial cumulative installed capacity of technology i, indicating the cumulative experience of technology i at the beginning.

In theory, the cost of energy extraction will increase with the depletion of resources, that is, the cost will increase over time but technological advances such as discoveries will also increase the number of new (or exploitable) resources every year. Advancements in mining technology will also reduce some of the costs. By combining these two points and considering the average price of coal for power generation from 1997 to 2007 provided by the China Coal Industry Association, the energy mining cost is assumed to increase gradually at a certain ratio.

Equation (15) shows the calculation of p_i^t, where z_i represents the amount of carbon dioxide emissions per unit of power generation of the technology I; this represents the emission coefficient of carbon dioxide emissions.

$$p_i^t = z_i x_i^t \tag{15}$$

3. Data source and processing

In order to ensure that the model is realistic, thermal power plants that use coal to generate electricity, gas turbine units that use natural gas to generate electricity (combined cycle power plants), and photovoltaic cells are selected in this study to represent traditional technologies, transition technologies, and revolutionary new technologies respectively. In the “2050 China Energy and CO_2 Emissions Report” (ERI, 2009b), these three technologies accounted for 70.6%, 0.5%, and less than 0.01% respectively of the total installed generating capacity in 2000 and the values were 55%, 2.7%, and 1.9% in the 2015 China Statistical Yearbook (CSY, 2014). As shown in Fig. 1, the installed capacity of gas turbine power generation and photovoltaic power generation increased by 24 times and 1326 times respectively, far exceeding other energy technologies; this indicates deduced that both gas turbines and photovoltaic cells have sufficient potential to be representative of transition technologies and new technologies.

In 2000, China's coal-fired and natural gas power generation installed capacity was 218.23 million kilowatts and 1.52 million kilowatts respectively, while the installed capacity of photovoltaic power generation was only 20,000 kW (ERI, 2009b). Assuming that the initial cumulative installed capacity of the three technologies is 5 times the total initial installed capacity, the initial cumulative installed capacity for coal, natural gas, and photovoltaic power generation is assumed to

be 1109.15 million kilowatts, 7.6 million kilowatts, and 100,000 kW respectively.

According to the Integrated Energy and Environment Policy Assessment Model for China (IPAC) database, the investment cost of China's existing supercritical units (thermal power) is around 3900 yuan/KW with an efficiency of 40%. The research by Yang (2004) shows that the investment cost of China's recently constructed combined cycle power plants (gas turbine power generation) is around 3100 yuan/KW with an efficiency of 60%. The study by Wang (2005) provides the initial investment composition per kilowatt of the flat-panel photovoltaic power generation grid-connected system in China in 2005. The initial investment cost is about 50,000 yuan/KW with an efficiency of 20%.

Jiao (2000) conducted a comparison of the power generation costs for several different power generation schemes and discussed the calculation method of the power generation cost of power plants. The operation and maintenance cost of supercritical units and combined cycle units was about 0.03 US dollars/kWh. The research by Wang et al. (2014) showed that the cost of solar power generation in 2010 was about 50% higher than that of the traditional power grid. It can be deduced from this trend that the operating and maintenance cost in 2000 was 0.05 US dollars/kWh.

Because of the different raw materials used in supercritical unit and the combined cycle power plant, the mining cost is different. In order to simplify the research, the average price of the power generation resources can be used to represent the mining cost. The China Coal Association lists the selling price of coal for power generation in China's state-owned coal mines from 2000 to 2007. The average selling price of coal is shown in Fig. 2. In 2000, the price was 120.93 yuan/ton. Excluding the effect of the price factor (discount rate), the mining cost can be assumed to increase at an annual rate of 5%. Similarly, the natural gas prices (CIF) in the international market rose from \$4.72/million BTU in 2000 to \$7.73/million BTU in 2007, which is the same annual rate of 5%.

The rate of China's future GDP growth can be predicted based on the current economic situation. In 2017, China's actual economic growth rate was 6.9%. Compared with a growth rate of more than 10% in 2000–2005 the economic growth rate has slowed down significantly. It can be deduced from the research of Yu et al. (2018) that the minimum growth rate of China's economy will be 6.5% in 2010–2020, 5.5% in 2020–2030, 4.5% in 2030–2040, and will maintain a growth rate of more than 3.5% in 2040–2100; this is in agreement with the general economic trend, as shown in Table 1. According to the IPAC, the implementation of a carbon tax has little impact on the GDP at a maximum of only 0.45%; therefore, GDP growth can be considered an exogenous variable (Jiang et al., 2000).

Duan et al. (2018) demonstrated that China has achieved the goal of reducing carbon emissions by 40% by 2020 earlier and can easily achieve a 60%–65% reduction in carbon emissions by 2030 (based on 2005). Therefore, the energy intensity is treated as an exogenous variable in this study. According to the constant price in 2005, the energy consumption per 10,000 yuan of GDP has dropped from 3.39 ton coal equivalent (tce) in 1980 to 1.31 tce in 2006 and the energy intensity curve has an exponential function, i.e., $y = 0.985e^{-0.04(10t-26)}$; the specific parameters are shown in Table 2.

McDonald and Schrattenholzer (2001) estimated and compared the learning rates of various new energy technologies and determined that the learning rates of gas turbines and photovoltaic solar technologies were around 10% and 20% respectively. In addition, others estimated that the learning rate of the integrated gasification combined cycle (IGCC) was 11% and 12% (Rubin et al., 2004; Mckincey, 2008), whereas Lohwasser and Madlener (2012) believed that the values should be between 7.1% and 12.2%. Based on these data, the learning rate of coal power was set to 8%, i.e., $1\text{-}2^{-b_i} = 8\%$, where $b_2 = 0.1$. The gas turbine learning rate was set to 10%, i.e., $1\text{-}2^{-b_i} = 10\%$, where $b_2 = 0.1520$. The learning rate of the photovoltaic power generation technology is set to 20%, i.e., $1\text{-}2^{-b_i} = 20\%$, where $b_2 = 0.32$.

The carbon dioxide emission coefficient in this study was based on the research of Liu et al. (2015). The conversion coefficient of the physical and tce is based on the data of the China National Bureau of Statistics (NBSC), as shown in Table A1 in the Appendix.

In order to investigate the effect of the carbon tax on the diffusion of energy technology, only two carbon tax rates were used in this study and they were based on the carbon tax levy standard of Denmark, Japan, and other countries and the research of Richard (2004). The carbon taxes were 50 yuan/(ton C) and 100 yuan/(ton C), representing a high carbon tax and low carbon tax respectively. In addition, the annual discount rate was set at 5%. The factory lifetime of the three technologies was assumed to be 30 years. The basic investment confidence λ was 10, indicating that the new installed capacity is at most 10 times higher than that of 10 years ago.

4. Simulation results

The model was programmed in MATLAB and the results were determined for 10-year periods. A total of 10 calculations were conducted and the change in energy technology diffusion was determined for 100 years. We used a processor with a CPU of CORE i5 6300HQ; the calculation speed was about 1.5 min and the time complexity of the model was low and within an acceptable range.

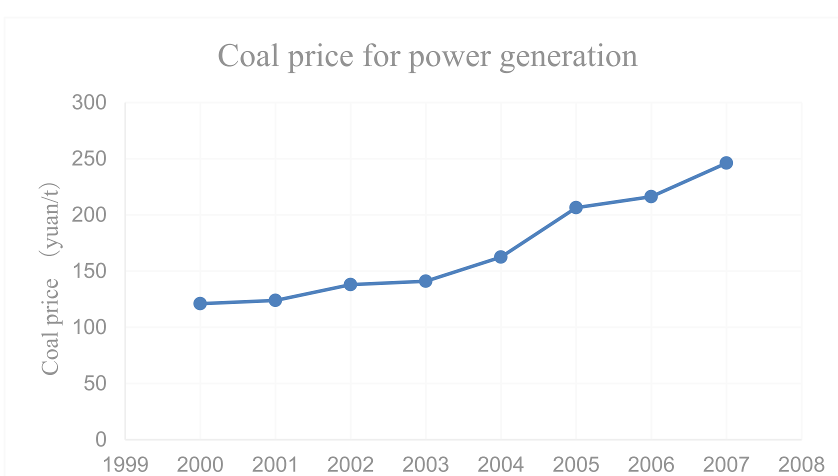

Fig. 2. Average coal price of China's state-owned coal mines.

Table 1
Annual growth rates of GDP for different periods.

Period	2010–2020	2020–2030	2030–2040	2040–2050	2050–2060	2060–2070	2070–2080	2080–2090	2090–2100
Growth rate (%)	6.5	6.5	5.5	4.5	4.5	3.5	3.5	3.5	3.5

Table 2
Time settings of Carbon intensity (tce/ten thousand Yuan).

Time	2000	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Carbon emissions	1.7	1.26	0.84	0.55	0.37	0.25	0.16	0.11	0.07	0.05	0.03

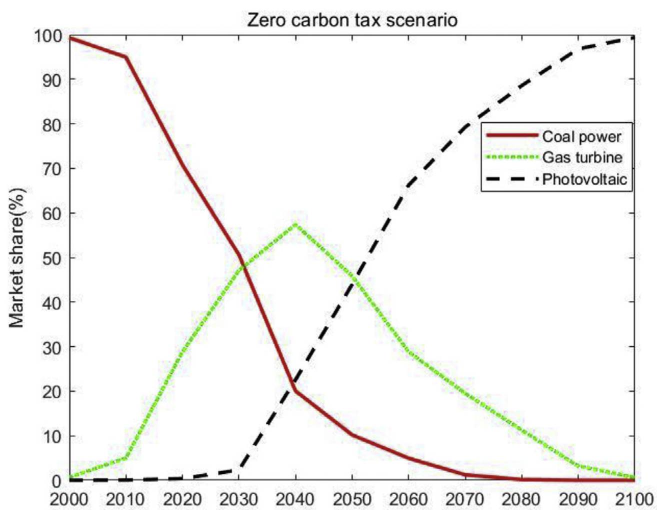

Fig. 3. Results of energy technology diffusion in a zero carbon tax scenario.

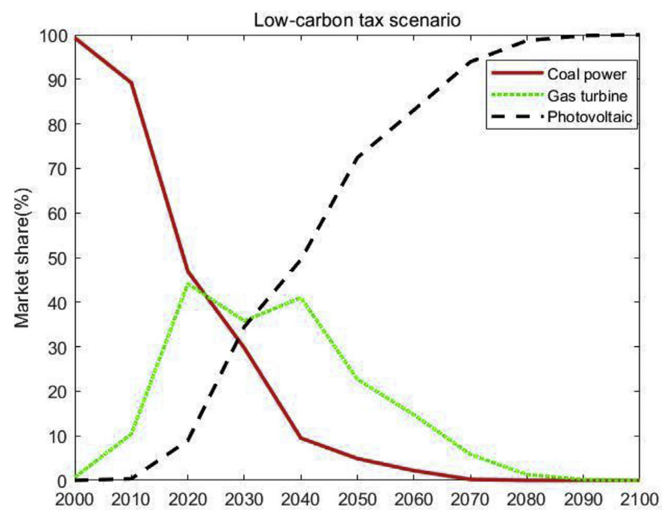

Fig. 4. Results of energy technology diffusion in a low-carbon tax scenario.

4.1. Zero carbon tax scenario

The zero carbon tax represents the basic scenario in this study. Fig. 3 shows the substitution effect of the three energy technologies in this scenario. The market share is the proportion of the installed capacity of each technology to the total installed capacity. Around 2030, gas turbines will dominate the power generation market and their market share will reach a peak of 57.4% in 2040. After that, the gas turbines will be replaced by photovoltaic power generation; this represents a process in which transition technology replaces traditional technology and is then replaced by new technology. The market share advantage of coal-fired power plants in the initial period is mainly due to their lower initial investment costs; the reason why gas turbines and photovoltaic power generation technologies exhibit great strength after the initial period is that they have a cost advantage due to the increase in cumulative installed capacity of the technology, which means that they quickly replace coal-fired power technology.

4.2. Carbon tax scenario

The carbon tax on carbon dioxide emissions increases the total cost of the technology, which has a large effect on coal-fired power plants with high-carbon emissions; therefore, coal-fired power plants are replaced sooner. Fig. 4 shows the substitution effect of energy technology in the low-carbon tax scenario. Compared with the carbon-free tax scenario, the market share of gas turbines and photovoltaic power generation is growing faster and the market share of photovoltaic power generation reaches 50.3% before 2040.

Increasing the carbon tax does not only have a more adverse impact on high-carbon emissions technologies but also increases investor confidence in environmentally friendly technologies such as photovoltaic power generation. Therefore, the growth rate of gas turbines and photovoltaic power generation technology is significantly different in the high carbon tax scenario, as shown in Fig. 5. The gas turbines reach a maximum market share of about 24.1% around 2020 and maintain a market share of more than 20% until 2040. However, the growth rate of the market share of the photovoltaic power generation is higher in the high carbon tax than the low carbon tax scenario. The market share of the photovoltaic power generation exceeds that of gas turbines in 2010–2020, maintains a rapid growth, and reaches 70.3% of the market share around 2040. This is similar to the actual situation. According to “Report of market prospective and investment strategy planning of China natural gas power industry” released by the Prospective Industry Research Institute (PIRI, 2018), the installed capacity of gas-fired power generation in 2016 was 77.14 million kilowatts but

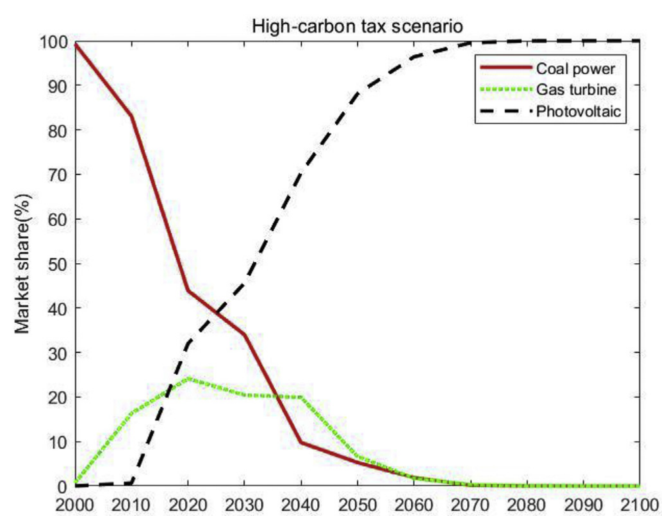

Fig. 5. Results of energy technology diffusion in a high-carbon tax scenario.

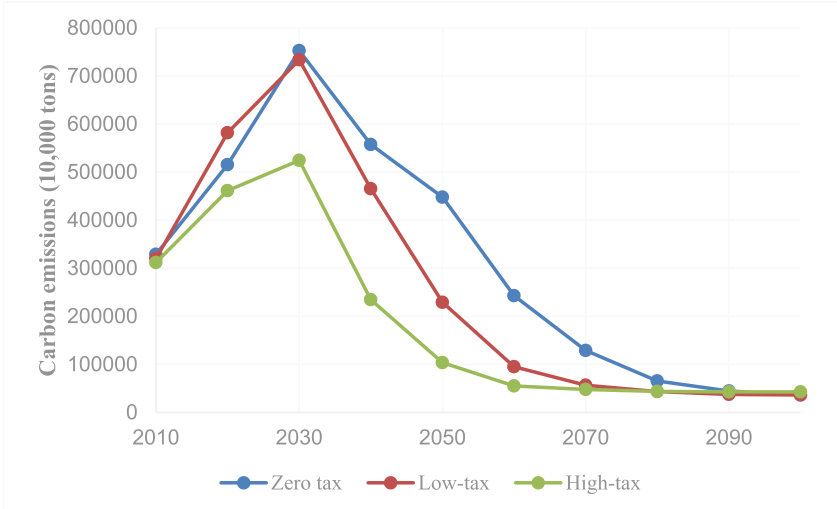

Fig. 6. Combined carbon emissions of the three energy technologies.

the figure for photovoltaic power generation was 77.42 million kilowatts in the same year.

In summary, the carbon tax on carbon emissions increases the power supply cost of the power generation plants and this is particularly apparent for high-polluting traditional thermal power plants. This results in the development and adoption of new technologies to replace traditional technologies. The higher the carbon tax, the more significant the effect is. The current situation of China's energy technology diffusion is located between the low carbon tax and high carbon tax scenarios.

4.3. Measurements of carbon emission peaks in the three scenarios

We calculated the energy consumption of the three technologies using the carbon dioxide emission coefficients to obtain the total amount of carbon emissions of China's three technologies in the three scenarios of zero carbon tax, low carbon tax, and high carbon tax (Fig. 6). China will achieve the peak of carbon emissions in 2030 in all cases. The difference is that the peak value gradually decreases with increases in the carbon tax from 7.53 billion tons for the zero carbon tax to 7.33 billion tons for the low carbon tax and 5.25 billion tons for the high carbon tax. The growth rate of the carbon emissions gradually decreases with the increase in the carbon tax; the growth rate decreases from 81.9% to 26.1% in the period of 2020–2030 and the growth rate of the high carbon tax also decreases from 48% to 13.7%. In addition, in 2020, the emissions of the low carbon tax scenario exceed those of the zero carbon tax scenario due to the rapid increase in installed capacity of gas turbines.

4.4. Model parameter sensitivity analysis

In the sensitivity analysis of the model parameters such as the discount rate and energy efficiency, it is found that the basic investment confidence, learning efficiency, and other parameters directly affect the energy technology diffusion. When λ has values of 15 and 20 in the low carbon tax scenario, in 2040, the proportion of photovoltaic power generation will reach 51.4% and 54% respectively, which is 1.1% and 3.7% higher than the initial value. It is evident that the improvement in basic investment confidence will promote the substitution of new technologies. In addition, in the low-carbon tax scenario, when the learning efficiency of gas turbines increases from 10% to 15%, the installed capacity still accounts for 26.6% of the market share in 2060, an increase of 12.7% compared to the learning efficiency of 10%. When the learning efficiency increases to 20%, the installed capacity of the gas turbines is maintained at a stable ratio of about 30%. It can be seen that the investment cost of the gas turbines decreases faster for higher learning efficiency, thus resulting in a total cost similar to that of photovoltaic power generation in the long term. In addition, energy technology substitution will be significantly slowed down by lowering the expected economic growth rate. For example, the market share of the transition technology and new technology in 2040 is reduced by 8.2% compared with the high expected growth rate under the zero-carbon tax scenario if the expected economic growth rate is reduced by 0.5%. It is evident that maintaining a high growth rate of the economy accelerates the development of new energy technologies.

5. Summary and policy implications

In this study, an energy technology diffusion model incorporating the energy-economy- environment relationship is established. This model not only has the advantages of an endogenous technology learning model but also considers the influences of government and investors with regard to irrational decision-making; this results in a more accurate model. By considering different carbon tax levels, the substitution effect of new energy technologies is quantitatively analyzed, and the carbon emission levels of China under different carbon tax scenarios are determined.

The simulation results show that the substitution of energy technology is a long-term and slow process. It takes decades for new energy technology, which is represented by photovoltaic power generation in this study, to gradually mature and become widely accepted. During this period, transition technologies such as gas turbines are developed but new technologies will eventually dominate the market. The carbon tax is an important means of using the market mechanism to reduce emissions. By increasing the power generation cost of high-carbon emission technologies and increasing the investor's investment confidence in low-pollution new technologies, the energy technology replacement process can be accelerated.

The results of the peak carbon emissions indicate that China will reach peak carbon emissions around 2030, regardless of the implementation of a carbon tax. However, the carbon tax level will affect the peak value and the rate of growth and decline in carbon emissions. A high carbon tax will undoubtedly and significantly reduce peak carbon emissions and the growth rate; these findings are similar to the research results of Yu et al. (2018).

The duration of the simulation is 100 years in this study, using a decade as the time period; this significantly reduces the computational complexity but is also insufficient in terms of the accuracy of the

results. Although the calculation of the peak carbon emissions shows that China reaches the peak of emissions in 2030, under the no carbon tax scenario, the carbon emissions exhibit an increasing trend. Therefore, considering the accuracy of the model, China may not be able to complete the target of reaching the peak before 2030 and the peak may be delayed by up to 5 years. In addition, raising the carbon tax significantly reduces the growth rate of carbon emissions and is, therefore, undoubtedly a more effective measure for China to improve its chances of achieving the expected goals. The Chinese government can set up a sound carbon tax system in the future or improve the trading mechanism of carbon emissions. Furthermore, subsidies for clean energy technologies are also an effective method to reduce the cost of new technologies and accelerate the substitution of energy technologies. The technology learning concept indicates that the earlier the new technologies are accepted, the more cost-effective these technologies are compared to traditional technology and the more likely it is for China to achieve the targeted carbon peak on time. Finally, the steady and rapid development of China's economy is also an important promoter of the application and development of new energy technologies; therefore, it is advisable to maintain a high economic growth rate to accelerate the diffusion process.

Since China does not have an absolute target of carbon emissions before 2030, the research has certain reference value for China to ensure the completion of the low-carbon development goals defined in the 13th Five-Year Plan and promote China's carbon dioxide emissions to achieve peak around 2030 and set corresponding specific emission targets in the future.

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Appendixes

Appendix A

Table A1
CO_2 emission coefficient of fossil fuels.

Fuels	CO_2 emission coefficient (ton CO_2/tce)
Coal	2.56
Natural gas	1.63

Table A2
Coefficient of kWh.

Units	Coefficient of kWh
British thermal unit	293.07 kWh/MBtu
Tons of coal equivalent	8130 kWh/tce

Appendix B

The conversion relationship between US dollar and RMB in this article is 1:7.1.

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